

The background features a light blue gradient. On the left, there is a stylized map of the Americas (North and South America) in a darker blue. Overlaid on the map and extending towards the left edge are white lines connecting various points, resembling a network or data flow. The main title is centered over the map.

Geostationary Satellites and Deep Learning

Presenter: Thomas Vandal

PI: Rama Nemani (GeoNEX)

Team Members: Weile Wang, Andrew Michaelis,
Jennifer Dungan, Hirofumi Hashimoto, Taejin Park,
Kate Duffy

Geostationary Virtual Sensors

Geostationary (GEO) satellite sensors are used to monitor the atmosphere, land, and oceans in high-frequency intervals

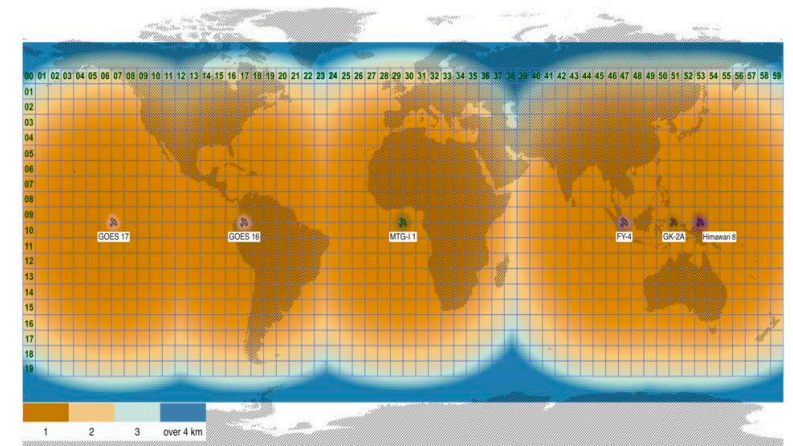
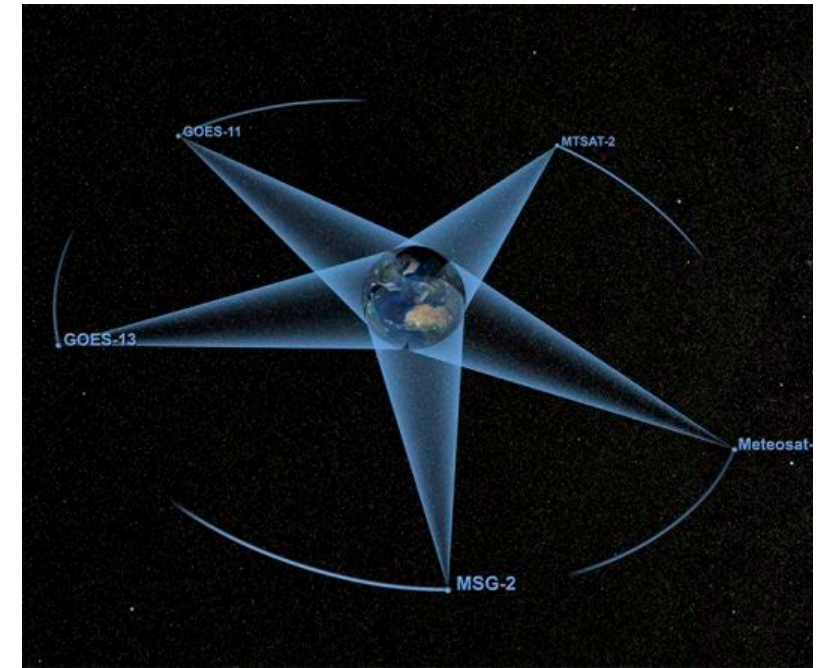
Imagery from multiple GEO sensors allows for near constant monitoring of large regions

Current sensors flying on GOES-16/17 (NOAA /NASA), Himawari-8 (Japan), GEO-KOMSAT-2A (South Korea)

Generates large amounts of data requiring efficient processing

Varying spectral coverage creates inconsistencies between images

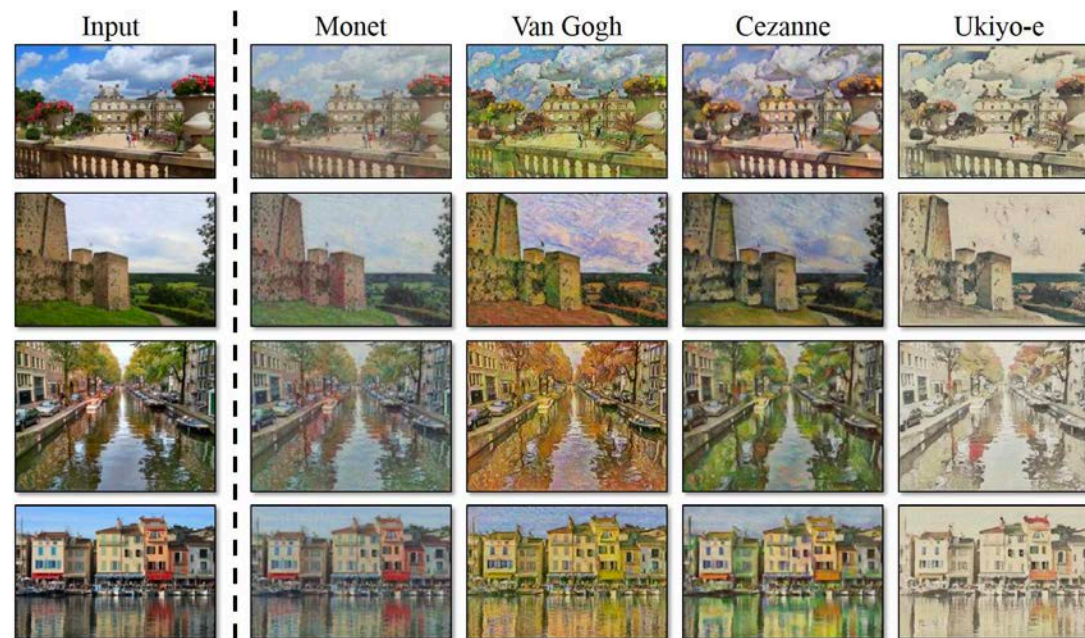
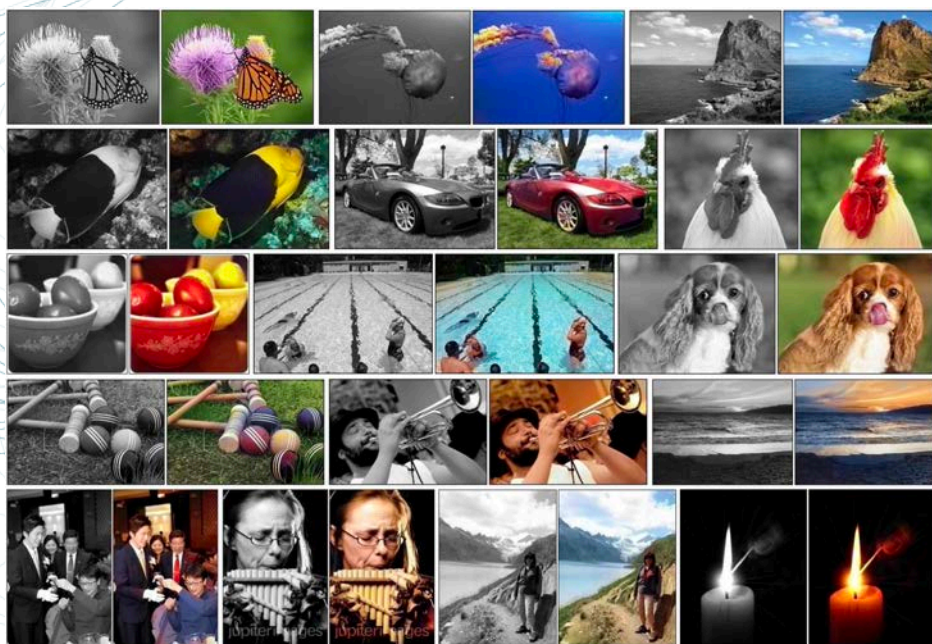
Current models for downstream products cannot be applied across sensors without significant model updates



Deep Learning for Image Translation

Image-to-image translation with deep learning has had tremendous success in generating realistic looking images

Tasks include: Image-colorization, style transfer, super-resolution, etc.

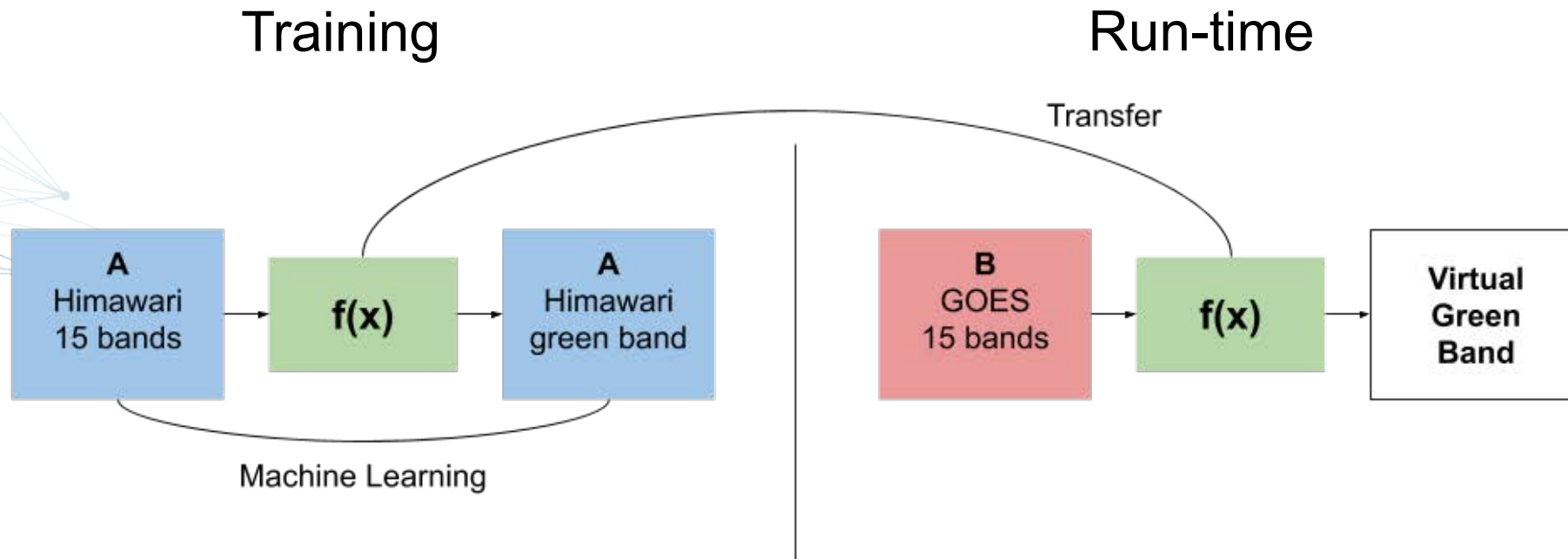


Applications to remote sensing: Cross satellite synchronization with virtual sensors, land and cloud segmentation, image denoising, and compression

Virtual Sensing - Supervised

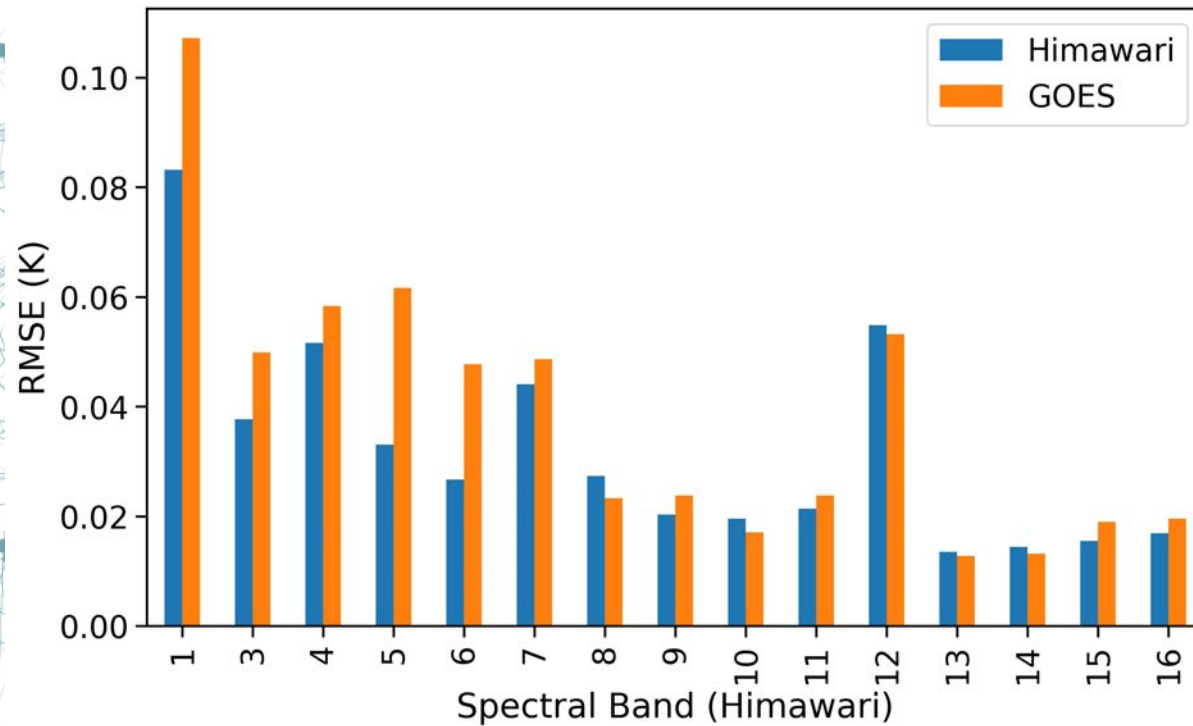
Given two satellites **A** and **B** with spectral bands, $\mathbf{A}=\{\alpha_1, \alpha_2, \dots, \alpha_K\}$ and $\mathbf{B}=\{\beta_1, \beta_2, \dots, \beta_K\}$ then $\mathbf{S} = \mathbf{A} \cap \mathbf{B}$.

Let, y to be some α_i not in \mathbf{S} , then a function $y \cong f(\mathbf{S})$ can be learned from **A** to **B**.

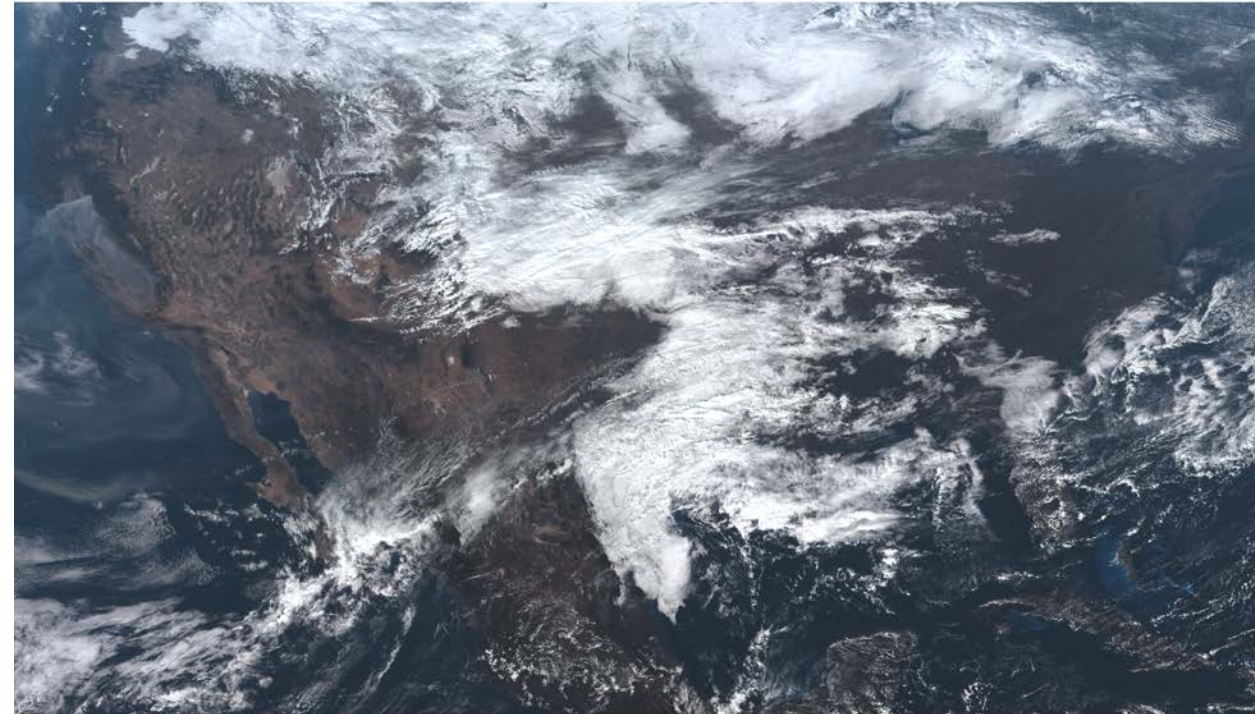


Results - GOES-16 and Himawari-8

Cross-validation Dropping Bands



GOES-16 True Color Image with virtual green band

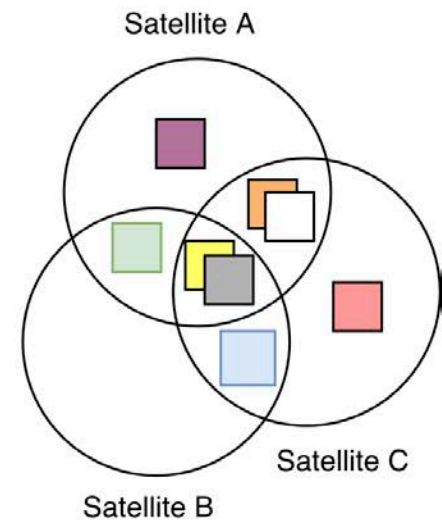
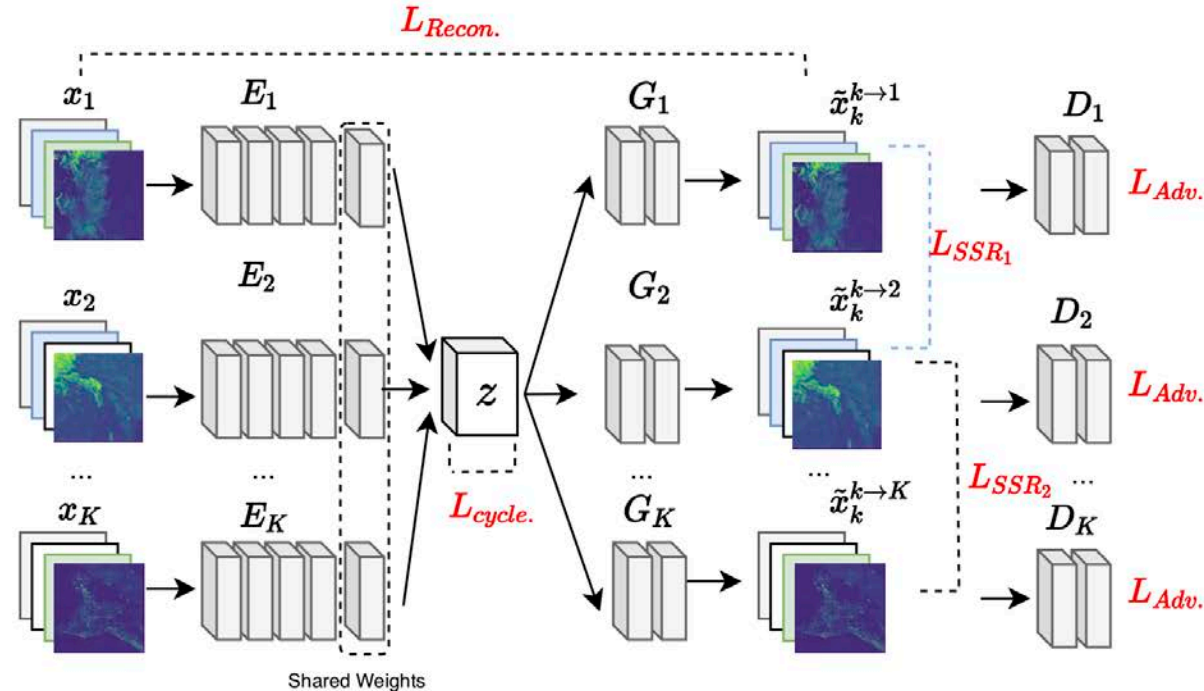


Virtual Sensing - Unsupervised

Paired images across sensors are often unavailable or limited but **large independent datastores are available**

Unsupervised Learning removes the dependence on labels and learns only from the inputs

Unsupervised Spectral Synthesis across geostationary satellites with a Variational Autoencoder and Generate Adversarial Network Architecture (Vandal 2020)



Downstream Cloud Detection (Unsupervised)

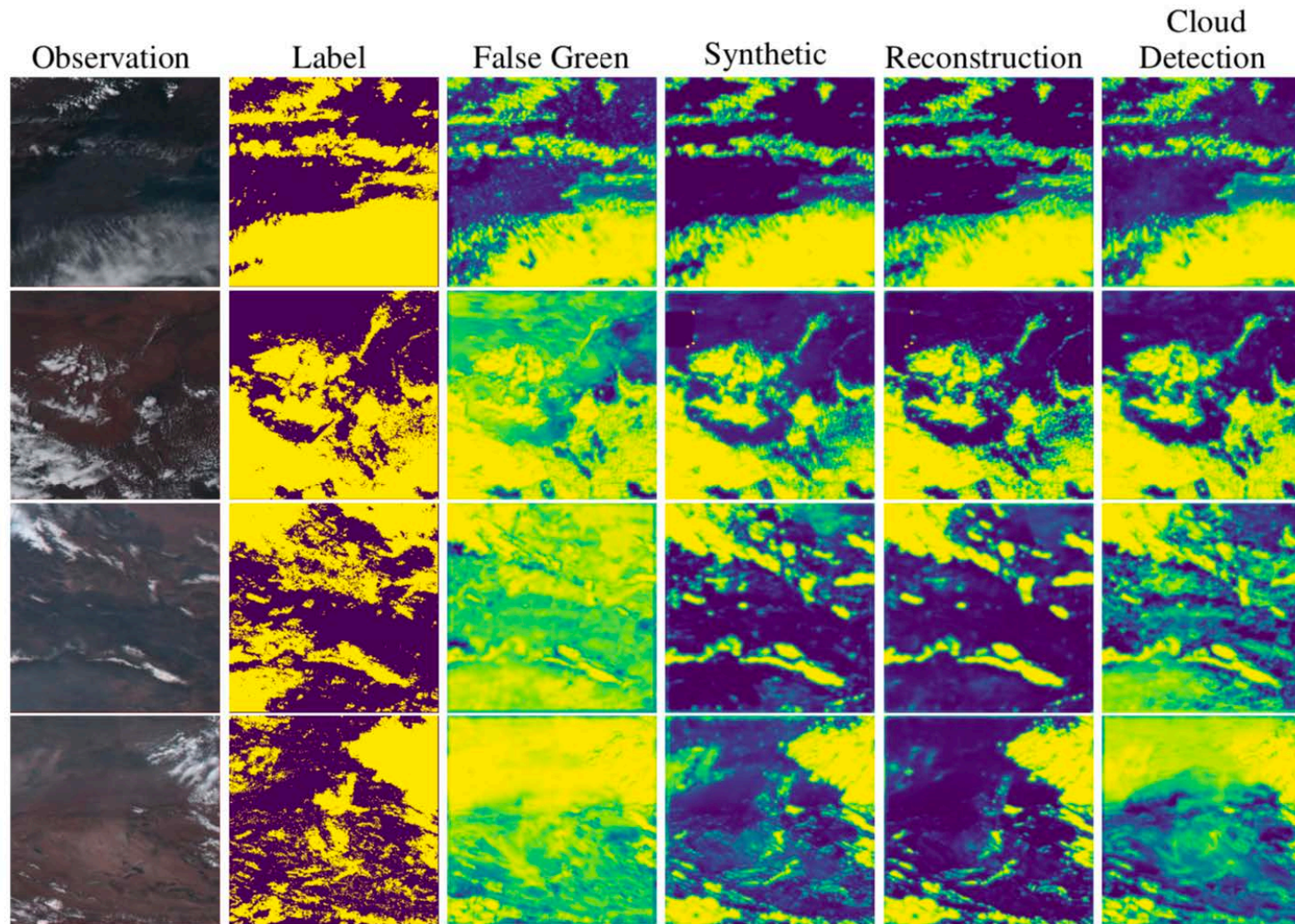
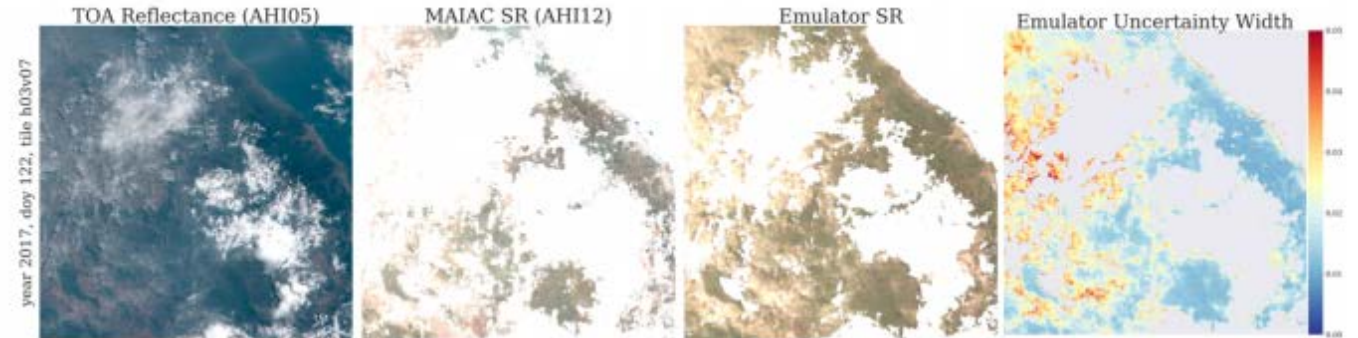


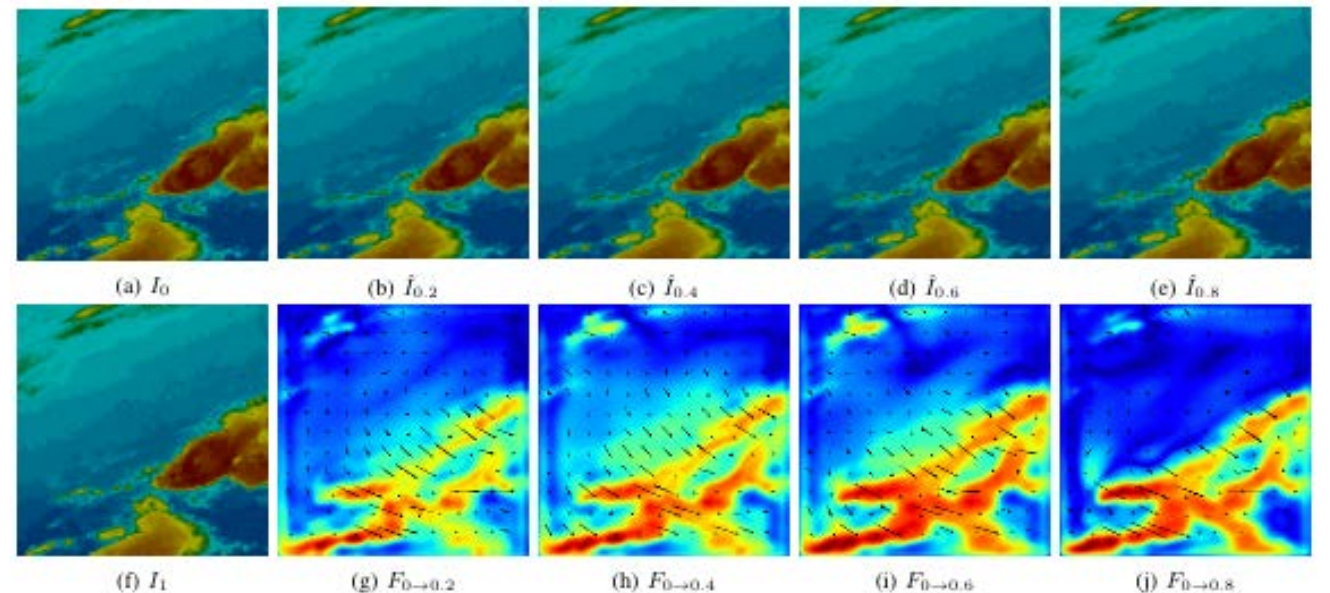
Figure 5: Cloud segmentation of four Himawari-8 observations. From left to right, columns show observation and cloud mask labels followed by false color, synthesized, reconstructed, and observed segmentation. Yellow denotes cloud pixels and blue non-cloudy pixels.

Related Applications

Emulation of computationally expensive physical models (Duffy 2019)



Atmospheric motion and temporal interpolation using optical flow (Vandal 2020)





Pros and Cons

Supervised Virtual Sensing

- ++ Produces fast and accurate approximations
- ++ Epistemic and aleatoric uncertainties captured
- Paired images are often unavailable for training
- Current approach uses Monte Carlo sampling at inference

Unsupervised Virtual Sensing

- ++ Unpaired datasets are widely available
- ++ Learns more generalizable and consistent models
- Optimization function is not well suited to high-resolution images
- Increased model complexity and computational requirements



Conclusions

Introduced supervised and unsupervised approaches to image-to-image translation tasks in remote sensing

Virtual sensors with deep learning can generate accurate estimates of synthetic bands in the supervised scenario

Unsupervised image-to-image translation is a promising approach to extend beyond paired datasets

Next steps

Extend applications of image-to-image translation to super-resolution, video processing, and segmentation tasks on remote sensing data.

Improve accuracies in unsupervised learning to compete with supervised models.



Back Up Slides

References

1. Vandal, T. & Nemani, R. (2019). “Optical Flow for Intermediate Frame Interpolation of Multispectral Geostationary Satellite Data”. [Arxiv](#). (In review)
2. Duffy, K., Vandal, T., Wang, W., Nemani, R., & Ganguly, A. R. (2019). Deep Learning Emulation of Multi-Angle Implementation of Atmospheric Correction (MAIAC). arXiv preprint arXiv:1910.13408. [Arxiv](#). (In review)
3. Vandal, T., McDuff, D., Wang, W., Michaelis, A., & Nemani, R. (2020). “Unsupervised Spectral Synthesis for Satellite-to-Satellite Translation.” (In review, NeurIPS)
4. Gao, N., Wilson, M., Vandal, T., Vinci, W., Nemani, R., & Rieffel, E. “High-Dimensional Similarity Search with Quantum-Assisted Variational Autoencoder,” Proceedings of the 26th ACM SIGKDD Conference on Knowledge Discovery and Data Mining (Research Track, 16% acceptance rate).